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Option Factor Momentum

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Abstract

We document significant time-series and cross-sectional momentum in 28 equity option factors. Factor momentum is distinct from a static factor portfolio, and prominent option factor models cannot fully explain its returns. Despite high autocorrelation, factor momentum profits are mainly driven by high and persistently different mean factor returns in the case of longer formation periods. Option factor momentum fully subsumes option momentum, but not vice versa. Our findings are robust over time, across various market states, and for alternative momentum strategy constructions.

I. Introduction

The existence of momentum, the continuation of past, relative asset returns into the future, has questioned market efficiency for over 30 years. The profitability of momentum strategies has been documented for various asset classes and investment regions.[1] Most recently, Heston, Jones, Khorram, Li, and Mo (2023) document momentum in option straddle returns.

Options constitute an asset class that has attracted considerable interest from practitioners and academics alike. According to data from the Options Clearing

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[1]See Jegadeesh and Titman (1993) for U.S. stocks, Rouwenhorst (1998) for international stocks, Miffre and Rallis (2007) for commodity markets, Jostova, Nikolova, Philipov, and Stahel (2013) for corporate bonds, and Liu, Tsyvinski, and Wu (2022) for cryptocurrencies.

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Corporation, the average daily volume amounted to 44.2 million contracts in 2023, compared to just 1.2 million contracts in 1996.[2] The study of the cross-section and prediction of delta-hedged option returns is still evolving, especially compared to the analogous literature on stock returns. In this context, as demonstrated by Käfer, Mörke, Weigert, and Wiest (2024) using Bayesian model averaging, option momentum is a likely part of the true stochastic discount factor that prices single-name options. Consequently, it is vital to deepen the understanding of the origins and characteristics of momentum in the options market.

To explain momentum profits, a new strand of literature focuses on momentum in factors that describe the cross-section of returns. Gupta and Kelly (2019) show that strong autocorrelation in equity factors results in profitable time-series (TSFM) and cross-sectional factor momentum (CSFM) strategies. Ehsani and Linnainmaa (2022) show that factor momentum subsumes stock momentum, and results by Arnott, Kalesnik, and Linnainmaa (2023) suggest that factor momentum also explains industry momentum. Crucially, factor momentum is a recent addition to possible explanations for momentum effects in financial markets.[3] On the contrary, Heston et al. (2023) find that a momentum strategy based on seven option factors cannot explain the momentum inherent in straddle returns. However, the authors concede that "[g]iven the relatively nascent literature on factors in option returns, it is possible that the factors we consider are an incomplete representation of the true factor structure" (Heston et al. (2023), p. 3178). Our article utilizes a larger set of 28 option factors shown to have explanatory power for the cross-section of (delta-hedged) option returns to construct option factor momentum strategies over the sample period from 1999 to 2021. Our main research goal is to study factor momentum's existence, characteristics, and drivers in the options market. Also, based on the advances in the stock momentum literature, we test if option factor momentum can explain option momentum.

We construct TSFM and CSFM strategies for option factors using various formation periods. For cross-sectional momentum (CSM) strategies, we assign a long position to factors with above-median returns during the formation period and a short position otherwise. For the time-series momentum (TSM) strategy, we assign the positions based on the sign of each factor's formation period return. Strategies are rebalanced monthly.

TSFM and CSFM strategies across all formation periods produce positive and statistically significant annualized mean returns, ranging from 6.46% (t-stat: 7.07) to 14.60% (t-stat: 10.65). The strategies offer returns distinct from an equal-weighted option factor portfolio, the 2-factor model by Zhan, Han, Cao, and Tong (2022), and the 3-factor model by Horenstein, Vasquez, and Xiao (2022), with high annualized information ratios (IRs) ranging from 0.82 to 2.88 for short and medium-term formation periods.

[2] https://www.theocc.com/market-data/market-data-reports/volume-and-open-interest/historical-volume-statistics, accessed on Jan. 25, 2024.

[3] Other explanations include behavioral-based explanations such as underreaction and overreaction theories (e.g., Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), and Grinblatt and Han (2005)), and risk-based explanations (e.g., Berk, Green, and Naik (1999), Pástor and Stambaugh (2003), Avramov, Chordia, Jostova, and Philipov (2007), and Kelly, Moskowitz, and Pruitt (2021)).

We conduct multiple momentum return decompositions to shed light on the drivers of option factor momentum. The hypothetical decomposition of CSM by Lo and MacKinlay (1990) emphasizes positive autocorrelation alongside negative cross-serial covariance and variation in mean returns as possible momentum drivers. We find that both autocorrelation and mean return variation significantly contribute to cross-sectional option factor momentum. Similarly, Moskowitz, Ooi, and Pedersen (2012) decompose a hypothetical TSM strategy into return autocorrelation and high mean returns. The second decomposition part indicates that high-mean factors consistently yield high returns independent of autocorrelation effects. Similar to the CSM decomposition, we document both channels as important sources of time-series option factor momentum, yet mean returns are more pronounced momentum drivers than return autocorrelation. These findings contrast the evidence in Ehsani and Linnainmaa (2022), who highlight autocorrelation as the main source of momentum in stock factors. Our results are similar to Leippold and Yang (2021), who demonstrate that a buy-and-hold strategy rather than factor timing largely explains TSFM for stocks. The buy-and-hold strategy is long (short) in factors with positive (negative) prevailing historical mean return. Therefore, it represents the contribution of high mean factor returns to TSM in contrast to the autocorrelation-related factor timing, which buys (sells) factors that outperform their prevailing historical mean. We show that a buy-and-hold strategy indeed explains a large part of TSM effects in option factors, although factor timing yields sizeable annualized Sharpe ratios between 0.67 and 0.80.

To test whether option factor momentum arises from option momentum or vice versa, we first construct equivalent momentum strategies on the option level. TSM strategies yield positive and significant profits for the 1-month, the 6-month, and the 1-year (excluding the most recent month) formation periods. Annualized mean returns for those strategies range from 4.45% (t-stat: 4.04) to 6.27% (t-stat: 4.70). For CSM, all strategies yield significant returns. Shorter-term option momentum is robust to controlling for the risk factors proposed by Horenstein et al. (2022). However, no option momentum alphas remain significant after augmenting the Horenstein et al. (2022) model with factor momentum returns. On the contrary, factor momentum remains significant across strategies even when controlling for the Horenstein et al. (2022) model augmented with option momentum, with t-statistics on the intercept ranging from 2.90 to 5.18. Our findings that option factor momentum subsumes single option momentum fall in line with the interpretation of option momentum as a historical risk premium as proposed by Tian and Wu (2023): The historical risk premium manifests itself in persistence and variation in risk exposures that drive option returns. As factor mean returns considerably contribute to the performance of option factor momentum strategies, the explanatory power of these strategies for single option momentum strengthens the view of a historical risk premium driving momentum effects in the options market.

Both in Ehsani and Linnainmaa (2022) and in Arnott et al. (2023), the largest principal components (PCs) of equity factors subsume the momentum in lower PCs and in the underlying factors. The authors argue that profitable autocovariance only exists in factors with high systemic risk. Otherwise, near arbitrage opportunities would exist. We transfer their tests to the option market and confirm that the momentum effects are the highest and most significant in the largest 7 PCs. These

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effects largely subsume momentum effects in the lower eigenvalue PC subsets. Additionally, high-eigenvalue PCs exhibit stronger explanatory power for momentum in single options.

Our results are robust to an alternative momentum strategy construction following Gupta and Kelly (2019), who weigh factors proportionally to their (risk-adjusted) past performance. Factor momentum returns remain highly significant and largely explain any of the profits of option momentum strategies constructed in the same way. Finally, these findings also hold for the vast majority of formation periods when constructing option factors and option momentum with delta-hedged put options instead of call options, when weighting options by their underlying market capitalization, or when excluding the least liquid options based on their proportional bid–ask spread.

Related Literature

Next to the option momentum documented by Heston et al. (2023) and the seminal work by Gupta and Kelly (2019), Ehsani and Linnainmaa (2022), and Arnott et al. (2023) on factor momentum, our article most and foremost relates to further studies on factor momentum effects. By focusing on the Chinese stock market, Ma, Liao, and Jiang (2024) provide evidence of factor momentum in international equity markets. Turning to asset classes other than stocks, Zhang (2022) finds that momentum in the dollar and carry factors subsumes currency momentum. Fieberg, Liedtke, Metko, and Zaremba (2023) document momentum effects in cryptocurrency anomalies. For commodity futures, Qian, Liu, and Jiang (2024) find factor momentum effects driven by mispricing. Lastly, Jiang, Ma, Wang, and Zhou (2024) find significantly positive factor momentum returns based on 10 corporate bond factors.

Second, our study also relates to the strand of literature that explains the cross-section of equity option returns. Many studies relate option returns and prices to various option and stock-related characteristics. Notably, Goyal and Saretto (2009) find that the difference between historical realized volatility and implied volatility, a general proxy for mispricing in the options market, negatively predicts future returns of straddles and delta-hedged call portfolios. Also, several studies highlight market frictions and required risk compensation of market makers as relevant drivers of option returns. For example, Cao and Han (2013) demonstrate that options on underlying stocks with high idiosyncratic volatility are more difficult to hedge and thus require higher returns by market makers, Christoffersen, Goyenko, Jacobs, and Karoui (2018) show that more illiquid options yield higher returns, and Tian and Wu (2023) can explain the variation in option returns using factors proxying for the risk of market making. Other studies focus on the impact of investors' behavioral biases on option returns: Bali and Murray (2013) find a negative relationship between option positions' risk-neutral skewness and returns, consistent with the notion of a positive skewness preference by investors. Moreover, Byun and Kim (2016) show that lottery-like properties of underlying stocks lead to overvaluation in call options as investors exhibit gambling preferences. Regarding option return anomalies without a clearly identified economic explanation, Zhan et al. (2022) provide evidence of predictability in the cross-section of

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delta-hedged option returns related to 10 stock-level characteristics, such as stock price, profitability, or cash holdings.

Given the abundance of characteristics with explanatory power for the cross-section of (delta-hedged) option returns, a large set of candidate factors exists for the options market. Our study exploits this large set of sorting variables introduced in the literature to construct option factors and option factor momentum strategies. Therefore, we contribute to the general literature on return anomalies and factors in the options market. Finally, analyzing option factor momentum enhances the understanding of factor autocorrelation and persistence in risk exposures that drive the returns and momentum of single equity options.

The rest of this article is structured as follows: In Section II, we describe the data sources, the definition of daily delta-hedged option return, and the option factor construction. In Section III, we present the main results of our baseline factor momentum strategies. In Section IV, we conduct various momentum decompositions to identify the main drivers of option factor momentum. We test for option momentum and perform the spanning tests between option and option factor momentum in Section V. In Section VI, we introduce and summarize the results of various additional analyses, such as PC momentum and robustness tests. Section VII concludes.

II. Option Data and Factor Construction

Our primary data source is OptionMetrics IvyDB, which provides historical prices for all U.S. single equity options. We obtain option prices and the interpolated volatility surface from OptionMetrics from Jan. 1996 to Dec. 2021. Volatility surface data is only required for constructing option-based characteristics, whereas option returns are based on historical option prices.

Historical prices for underlying stocks are obtained from CRSP. We retain only underlying stocks with share codes 10 or 11. Moreover, we exclude stocks with a prior month's closing price below USD 5 to avoid options on highly illiquid underlying stocks. We match CRSP with OpionMetrics using the linking algorithm provided by WRDS. Daily risk-free rates are taken from Kenneth French's online data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

A. Option Returns

We use the excess return of buying a delta-hedged call option on a daily rebalancing schedule to construct option factor returns. In line with previous literature (e.g., Horenstein et al. (2022)), we focus on call options in our analyses as these contracts have a higher volume than puts (Bollen and Whaley (2004)).[4] For the computation of delta-hedged returns, we first consider delta-hedged call gains following Bakshi and Kapadia (2003) as the value of a self-financing portfolio consisting of a long call that is hedged by a position in the underlying such that the portfolio is locally immune to changes in the stock price. We choose a daily

[4]Our key results also hold for option factor strategies constructed with delta-hedged put returns (see Section VI.D).

delta-hedging schedule as Tian and Wu (2023) document that delta-hedging at position initiation removes approximately 70% of the directional risks embedded in the option position, whereas daily delta-hedging yields a reduction of 90%. To establish notation, consider the partition $\Pi = \{t = t_0 < \cdots < t_N = t + \tau\}$ of the interval from t to $t+\tau$. Assume that the long option position is hedged discretely N times at each date $t_n, n = 0, \ldots, N-1$. The discrete delta-hedged call option gain over the period $[t, t+\tau]$ is then given by

$$\text{(1)}\quad \Pi(t, t+\tau) = C_{t+\tau} - C_t - \sum_{n=0}^{N-1} \Delta_{t_n} [S(t_{n+1}) - S(t_n)] - \sum_{n=0}^{N-1} \frac{a_n r_n}{365} [C_t - \Delta_{t_n} S(t_n)],$$

where C_t denotes the price of the call option at time t, r_n is the risk-free rate at t_n, a_n is the number of calendar days between the re-hedging dates t_n and t_{n+1}, which we set to $a_n = 1$, and Δ_{t_n} is the observed delta of the call as provided by OptionMetrics. The last term in equation (1) is the return on the position's net cash investment. We consider gains for investment horizons of 1 calendar month. Subsequently, we define option returns following Cao and Han (2013) as

$$\text{(2)}\quad r_{t,t+\tau} = \frac{\Pi(t, t+\tau)}{\Delta_t S_t - C_t},$$

where we scale the delta-hedged option gains by the absolute values of the securities involved in initiating the position.[5]

B. Option Filters

We closely follow the filters of Zhan et al. (2022) and Bali, Beckmeyer, Mörke, and Weigert (2023) to obtain our final option sample, from which we construct characteristics-based option portfolios. We follow Bali et al. (2023) and apply filters only at position initiation. This mitigates any forward-looking bias, which can significantly affect option returns, as pointed out by Duarte, Jones, Mo, and Khorram (2024). If no option price is available at the time of position closing, we use the intrinsic value of the option (Bali et al. (2023)). First, at the end of each month and for each stock, we select the call option closest to being at-the-money, which has the shortest maturity among contracts that do not expire in the next month. Second, we only retain calls if the underlying stock did not pay dividends

[5]We consider 3 alternative definitions of the option return and the discrete delta-hedged call gain in Section D of the Supplementary Material and show that option factor momentum is robust to these choices. First, equation (1) does not account for compound interest in the net cash balance. We derive an alternative definition of the discrete delta-hedged gains accounting for compounding and show additional baseline results in Section D.1 of the Supplementary Material. Second, the Black-Scholes delta is subject to model risk and does not necessarily minimize the variance of the changes in the hedge portfolio if, e.g., there is a nonzero correlation between changes in volatility and prices (Hull and White (2017)). The minimum variance delta is the position in the underlying that minimizes the variance of the changes in the value of the hedge portfolio. We adopt an empirically derived minimum variance delta proposed by Hull and White (2017). Details and additional results are given in Section D.2 of the Supplementary Material. Third, daily-delta hedging may lead to momentum in factors if gains due to short-term reversals of underlying stocks are asymmetric and persistent in the long and short legs of factors. To account for this effect, we show results using initial delta-hedging in Section D.3 of the Supplementary Material.

during the month-end to month-end investment period. Third, we only keep option observations with an implied volatility estimate in the OptionMetrics data. Fourth, we only keep options with positive outstanding open interest and a positive bid quote, a bid price strictly smaller than the ask price, a mid-price between the ask and bid quote of at least USD 0.125, and a proportional bid–ask spread below 50%. Fifth, we exclude observations that violate clear no-arbitrage conditions for American call options such as $S \geq C \geq \max(0, S - Ke^{-rt})$. Sixth, we exclude options with a strike-to-spot ratio, K/S, lower than 0.8 or larger than 1.2. As most options at the end of each month have the same maturity, we discard observations with different expiration dates from most other options selected on that day. Finally, for the remaining calls in our sample, we compute daily rebalanced delta-hedged returns from the selection month's end to the end of the following month using equations (1) and (2).

Table A.1 in the Supplementary Material shows summary statistics for our final pooled sample of monthly call option observations. In total, the sample contains 379,165 option-month observations for 7015 unique underlyings. On average, our sample consists of 1219 unique underlying stocks per month. The average daily delta-hedged option return is −0.12%, in line with a negative volatility risk (VR) premium inherent in delta-hedged option returns (Bakshi and Kapadia (2003)).

C. Option Factors

We construct option factors using various stock and option contract-level characteristics. In particular, we consider characteristics that exhibit explanatory power for option returns in stand-alone academic papers. We provide details on 28 characteristics and their construction in Section B of the Supplementary Material. These characteristics are, in some cases, based on option data such as the option bid–ask spreads (OPTSPREAD, Christoffersen et al. (2018)) or the term structure of at-the-money implied volatility (IVTERM, Vasquez (2017)). However, in most cases, the sorting variables are based on stock data, such as the risks to market-making introduced by Tian and Wu (2023). A characteristic based on both stock and options data is the difference in the option's implied volatility and the realized volatility of the underlying stock (IVRV, Goyal and Saretto (2009)).

Based on these characteristics, we construct monthly option factors by sorting all available options at the end of each month into equal-weighted deciles. To determine the long and short deciles, we neither use the full-sample mean of the factors nor rely on factor signs from previous studies, as this would introduce a look-ahead bias. Instead, we use an expanding window with an initial burn-in period from 1996 to 1998 to determine long and short deciles. To do so, we compare the prevailing historical mean return of deciles 1 (low characteristic values) and 10 until factor construction at time t and use the decile with the higher (lower) return as the long (short) leg.[6] This approach allows real-time identification of the direction of decile sorts that have historically yielded positive returns. Consequently, our main option factor sample in our empirical analyses spans 1999 to 2021.

[6]Our main results are robust to the choice of burn-in period lengths from 1 to 5 years.

TABLE 1

Overview of Individual Factor Returns

Table 1 reports the mean ($\mathbb{E}[F]$), standard deviation (SD), and Sharpe ratio (SR) of monthly returns for each of our 28 option factors. t-statistics of mean returns account for heteroskedasticity and autocorrelation in residuals up to lag 4, following Newey and West (1987). Factors are constructed by monthly characteristic-based sorts of delta-hedged call options into deciles. We determine the sorting direction of the characteristics-based long-short portfolio using an expanding window with a burn-in period from 1996 to 1998. The sample period is from Jan. 1999 to Dec. 2021. Detailed descriptions of the characteristics used for factor construction are documented in Section B of the Supplementary Material.

Factor	Reference Paper	$\mathbb{E}[F]$	$t(\mathbb{E}[F])$	SD	SR
1. Embedded leverage (EMBEDLEV)	Frazzini and Pedersen (2022)	0.47	7.42	0.77	0.61
2. Delta-hedging costs (HC)	Tian and Wu (2023)	0.74	5.31	1.66	0.45
3. Volatility risk (VR)	Tian and Wu (2023)	1.01	7.71	1.71	0.59
4. Historical jump risk (JR)	Tian and Wu (2023)	0.92	11.56	1.20	0.77
5. Volatility of implied volatility (VOV)	Ruan (2020)	0.40	4.59	1.22	0.32
6. Option illiquidity (OPTSPREAD)	Christoffersen et al. (2018)	0.10	1.17	1.23	0.08
7. Historical stock volatility (HVOL)	Hu and Jacobs (2020)	0.70	4.26	2.09	0.34
8. Systematic volatility (SYSVOL)	Aretz, Lin, and Poon (2023)	−0.05	−0.30	2.15	−0.02
9. Impl. ATM vol term struct. (IVTERM)	Vasquez (2017)	0.91	6.80	1.71	0.53
10. Stock return autocorrelation (AC)	Jeon, Kan, and Li (2025)	0.00	−0.08	0.91	−0.01
11. Average of 10 highest past returns (MAX10)	Byun and Kim (2016)	0.52	3.11	2.22	0.23
12. Default risk (DEFRISK)	Vasquez and Xiao (2024)	0.14	0.85	1.80	0.08
13. Idiosyncratic skewness (ISKEW)	Byun and Kim (2016)	0.07	1.17	0.89	0.08
14. Total skewness (TSKEW)	Byun and Kim (2016)	0.13	1.57	1.00	0.13
15. Idiosyncratic volatility (IVOL)	Cao and Han (2013)	0.83	5.84	1.85	0.45
16. Implied minus realized volatility (IVRV)	Goyal and Saretto (2009)	2.31	10.23	2.19	1.05
17. Stock illiquidity (AMIHUD)	Zhan et al. (2022), Kanne, Korn, and Uhrig-Homburg (2023)	0.43	3.10	1.59	0.27
18. Short interest (RSI)	Ramachandran and Tayal (2021)	0.13	1.66	1.14	0.11
19. 1-year new stock issues (ISSUE_1Y)	Zhan et al. (2022)	0.42	3.62	1.44	0.29
20. 5-year new stock issues (ISSUE_5Y)	Zhan et al. (2022)	0.65	5.65	1.39	0.47
21. Analyst dispersion (DISP)	Zhan et al. (2022)	0.29	3.34	1.14	0.25
22. Altman Z-score (ZSCORE)	Zhan et al. (2022)	0.24	2.24	1.42	0.17
23. Cash-to-assets ratio (CASH_AT)	Zhan et al. (2022)	0.79	5.95	1.67	0.47
24. Cash flow volatility (OCFQ_SALEQ_STD)	Zhan et al. (2022)	0.91	8.52	1.47	0.62
25. Operating profits/book equity (OPE_BE)	Zhan et al. (2022)	0.81	7.30	1.59	0.51
26. Profit margin (EBIT_SALE)	Zhan et al. (2022)	0.90	7.76	1.57	0.57
27. Net total issuance (NETIS_AT)	Zhan et al. (2022)	0.52	4.39	1.63	0.32
28. Stock price (LOG_PRICE)	Zhan et al. (2022), Boulatov, Eisdorfer, Goyal, and Zhdanov (2022)	1.00	6.16	1.77	0.56

Table 1 presents an overview of the mean returns ($\mathbb{E}[R]$) of the 28 option factors in percentages. t-statistics are based on standard errors robust to heteroskedasticity and autocorrelation in residuals up to the fourth lag following Newey and West (1987). Overall, 21 of 28 mean factor returns display t-statistics above 2. In addition, the magnitude of returns is large, with up to 2.31% per month (IVRV), highlighting the strong predictive power of certain sorting characteristics for delta-hedged returns.

Additionally, we present factor autocorrelations in Figure 1. Significant autocorrelation in factor returns is a main indicator and driver of factor momentum effects. The gray bars in Figure 1 show the Pearson correlation coefficients ρ between factor i's return in month t, $F_{i,t}$, and the same factor's average return over the formation period $-t$, $F_{i,-t}$. We depict 3 different formation periods: $t-1$ (month-on-month), $t-2$ to $t-12$ (year-on-month with the omission of the most recent month), and $t-13$ to $t-60$ (long-term autocorrelation, potentially testing for long-term reversal). 95% confidence intervals are depicted in black.

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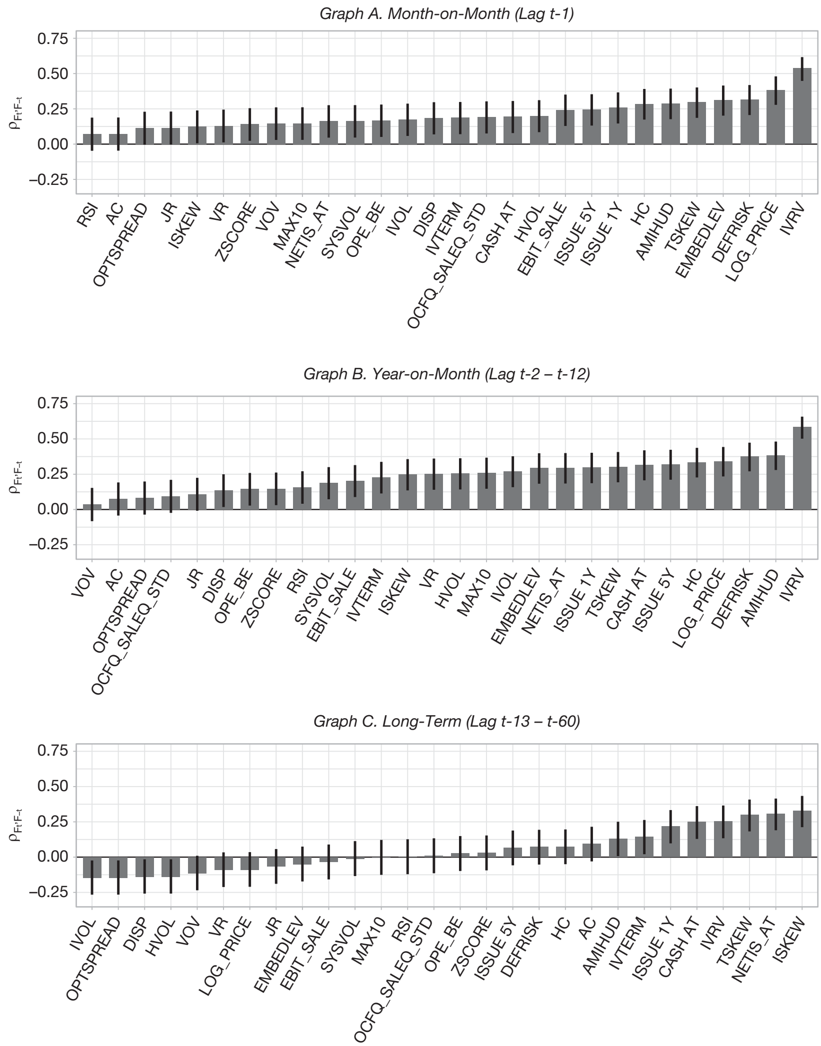
FIGURE 1

Autocorrelation of Individual Factor Returns

Figure 1 shows autocorrelation coefficients (gray bars) between factor returns and their past returns over various formation periods. The black lines represent 95% confidence intervals. The sample period is from Jan. 1999 to Dec. 2021. Detailed descriptions of the characteristics used for factor construction are documented in Section B of the Supplementary Material.



For the formation month $t-1$, we document significantly positive ρ-coefficients for 24 out of 28 factors with a maximum correlation of above 50%, indicative of short-term momentum rather than reversal effects.

In the 1-year formation period, 23 of 28 factors still exhibit positive autocorrelation.

Finally, as depicted in Graph C, there is mostly no evidence of long-term autocorrelation or reversal for a 5-year formation period.

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III. Baseline Strategies and Factor Momentum Performance

Using the 28 option factors, we construct TSFM and CSFM strategies with monthly rebalancing. For the TSFM strategies, we assign long and short positions based on the sign of each factor's formation period return. For the CSFM strategy, we assign a long position to a factor with an above-median return in the formation period and a short position otherwise. We consider a holding period of 1 month and 4 formation periods ranging from the prior month up to 60 months minus the most recent 12 months. Formally, the TSFM return in month t with the formation period $-t$ is defined as

$$R_t^{TSFM} = \frac{2}{N}\sum_{i=1}^{N} \operatorname{sign}(F_{i,-t})F_{i,t}. \tag{3}$$

For CSFM, the return is given by

$$R_t^{CSFM} = \frac{2}{N}\sum_{i=1}^{N} \operatorname{sign}\left(F_{i,-t} - \tilde{F}_{-t}\right)F_{i,t}, \tag{4}$$

where $\tilde{F}_{-t}$ is the median formation period return. These strategies and formation periods are standard in the literature (see, e.g., Arnott et al. (2023), Gupta and Kelly (2019)). We consider both strategies because TSM strategies rely on performance continuation, while cross-sectional strategies also bet on relative performance continuation. Note that there are always $N/2$ factors in the long and short portfolios for the cross-sectional strategy. Long and short legs can be imbalanced in the time-series strategy, conditional on the average formation period performance.

We report annualized mean returns and Sharpe ratios for both TSFM and CSFM in Panel A of Table 2. We rely on GMM and the Delta Method to estimate the standard errors of the Sharpe ratios. For TSFM, annualized mean returns are all positive and significant, ranging from 10.51% (t-stat: 7.79) for the 1-month formation period to 14.60% (t-stat: 10.65) for the 12-month formation period, excluding the most recent month. Sharpe ratios are exceptionally high and range from 2.05 to 3.18. The economic magnitude of these results is not surprising, as individual factors already exhibit high Sharpe ratios (see Table 1). For CSFM, the raw performance is marginally worse due to the net-zero weight in well-performing factors. In contrast, TSFM is also long in below-median factors with positive returns on average.

Figure 2 shows the cumulative sums of monthly returns of the long and short legs of the TSFM and CSFM strategies.

Both strategies manage to identify factors with above-average subsequent performance, even when formation periods are short. Higher returns of the long legs compared to a long-only strategy that invests equally in all 28 option factors (EW_FAC) illustrate this fact. Second, the performance of the long legs is extremely high, with almost no drawdown periods and little volatility. TSFM strategies successfully identify factors with subsequent negative returns. Finally, for medium-term formation periods, the long and short legs of the CSFM strategies achieve higher returns than those of the TSFM strategies. Because more factors are

TABLE 2

Performance of Option Factor Momentum

Table 2 reports performance measures of both time-series factor momentum (TSFM) and cross-sectional factor momentum (CSFM) strategies based on 4 formation periods. All strategies are built from a set of 28 option factors with monthly returns from Jan. 1999 to Dec. 2021. TSFM strategies go long (short) in factors with positive (negative) formation period returns. CSFM strategies go long (short) in factors with an above (below) median formation period return. The strategies are rebalanced monthly, and the sum of absolute factor weights in both TSFM and CSFM strategies sum to 2. Panel B reports the results of regressing both TSFM and CSFM strategies on an equal-weighted portfolio of the 28 option factors with monthly rebalancing (EW_FAC). In Panel C, we use the factor model by Zhan et al. (2022) (ZHCT) consisting of factors based on liquidity (AMIHUD) and the option underlyings' idiosyncratic volatility (IVOL). In Panel D, we use a factor model based on Horenstein et al. (2022) (HVX) which includes the equal-weighted return of 280 decile portfolios from characteristic sorts (EW_RET), the volatility of implied volatility (VOV), and the difference in implied and realized volatility (IVRV). Mean returns (%), alphas (%), and Sharpe and information ratios (IRs) are annualized. All *t*-statistics (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag 4, following Newey and West (1987).

	Time-Series Factor Momentum (TSFM)				Cross-Sectional Factor Momentum (CSFM)			
	t–1	*t*–6	*t*–2 to *t*-12	*t*–13 to *t*–60	*t*–1	*t*–6	*t*–2 to *t*–12	*t*–13 to *t*–60
Panel A. Performance of Factor Momentum								
Mean Return	10.51	14.18	14.60	12.12	6.46	9.18	9.51	6.95
	(7.79)	(10.79)	(10.65)	(9.12)	(7.07)	(10.59)	(10.31)	(10.65)
Sharpe Ratio	2.05	3.09	3.18	2.67	1.72	2.74	2.95	2.37
	(9.96)	(11.31)	(12.11)	(7.77)	(8.49)	(11.00)	(14.66)	(8.73)
Panel B. Factor Momentum Versus Equal-Weighted Factors								
α	3.65	5.19	4.63	1.22	4.29	6.99	6.39	2.79
	(2.37)	(3.40)	(3.64)	(1.44)	(3.15)	(4.84)	(4.77)	(3.00)
EW_FAC	0.98	1.29	1.43	1.70	0.31	0.31	0.45	0.65
	(5.13)	(6.51)	(10.05)	(14.42)	(2.54)	(2.31)	(3.05)	(3.92)
R^2	0.24	0.51	0.63	0.85	0.04	0.06	0.12	0.30
IR	0.82	1.61	1.66	0.69	1.17	2.15	2.12	1.14
Panel C. Factor Momentum Versus ZHCT Factors								
α	7.96	10.30	10.27	5.68	6.33	9.23	8.87	4.21
	(5.71)	(7.83)	(7.82)	(4.77)	(4.94)	(8.20)	(8.60)	(7.14)
AMIHUD	0.36	0.30	0.30	0.10	0.20	0.17	0.16	0.03
	(4.29)	(4.68)	(4.49)	(1.21)	(2.75)	(3.09)	(2.85)	(0.53)
IVOL	0.07	0.23	0.28	0.59	−0.09	−0.09	−0.02	0.25
	(0.60)	(1.90)	(2.65)	(5.89)	(−0.94)	(−1.04)	(−0.30)	(4.84)
R^2	0.17	0.30	0.36	0.64	0.08	0.08	0.07	0.27
IR	1.71	2.69	2.81	2.08	1.76	2.88	2.85	1.69
Panel D. Factor Momentum Versus HVX Factors								
α	6.59	8.50	6.51	5.88	3.96	4.78	3.78	4.32
	(4.86)	(6.38)	(5.25)	(3.82)	(3.88)	(5.12)	(4.11)	(3.37)
EW_RET	−0.03	−0.13	−0.11	−0.21	0.09	0.09	0.13	−0.05
	(−0.31)	(−1.26)	(−0.82)	(−1.08)	(1.34)	(1.67)	(2.27)	(−0.48)
VOV	0.01	0.23	0.23	0.23	−0.06	0.06	0.05	−0.08
	(0.09)	(1.50)	(1.68)	(1.70)	(−0.92)	(1.00)	(0.85)	(−1.12)
IVRV	0.14	0.16	0.25	0.21	0.11	0.15	0.21	0.13
	(2.98)	(3.92)	(6.46)	(2.26)	(2.96)	(6.24)	(7.92)	(2.31)
R^2	0.04	0.18	0.28	0.24	0.07	0.16	0.30	0.08
IR	1.31	2.04	1.67	1.49	1.09	1.56	1.40	1.54

in the long leg for TSFM, the return attribution of high-performing factors is more diluted. However, this does not automatically disadvantage TSFM strategies, as their long leg is given higher overall weight.

Due to the long bias in the TSFM strategies, returns may likely be picking up on the returns of the long-only equal-weighted factor investing strategy. We test this by regressing TSFM and CSFM returns on EW_FAC. Additionally, we control the factor momentum strategies for factors based on two prominent low-dimensional option factor models. Following Zhan et al. (2022) (ZHCT), we control for risk

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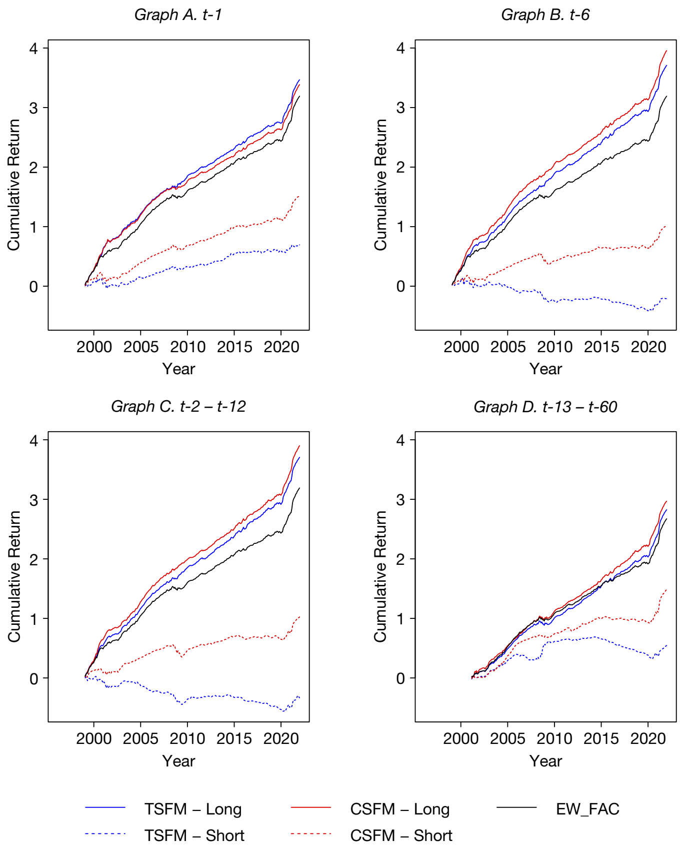
FIGURE 2

Cumulative Returns of Factor Momentum Legs

Figure 2 plots the cumulative sum of monthly returns of both time-series factor momentum (TSFM) and cross-sectional factor momentum (CSFM) strategies based on 4 formation periods as defined in equations (3) and (4). All strategies are built from a set of 28 option factors with monthly returns from Jan. 1999 to Dec. 2021. EW_FAC denotes a strategy that equally invests in all 28 factors with monthly rebalancing.



captured by factors based on the liquidity of the options' underlying (AMIHUD) and the underlyings' idiosyncratic volatility (IVOL). Following Horenstein et al. (2022) (HVX), we control for option market risk with an equal-weighted portfolio of all 280 decile portfolios used in the factor construction (EW_RET), as well as for two factors based on the volatility of implied volatility and the difference between implied and realized volatility (IVRV).

As reported in Panel B of Table 2, all but the long-term TSFM strategy yield positive and statistically significant alphas at the 1% level after controlling for the equal-weighted factor portfolio, EW_FAC. Even though alphas decrease relative to mean returns, high annualized IRs provide evidence that option factor momentum increases the investment opportunity set as these ratios are equal to Sharpe ratios after orthogonalizing TSFM and CSFM returns to the control factors (Haddad, Kozak, and Santosh (2020)). TSFM strategies converge to static factor investing the

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longer the formation period with a high R^2 of 0.63 for the $t-2$ to $t-12$ strategy and 0.85 for the $t-13$ to $t-60$ strategy. This is not the case for CSFM with R^2 ranging from 0.06 to 0.30.

Alphas are positive and statistically significant when controlling for the ZHCT factors, with t-statistics ranging from 4.77 to 8.60. The annualized IRs are highest for the medium-term formation periods, reaching 2.88 for the $t-6$ CSFM strategy. Similar results arise when controlling for the HVX factors in Panel D. Although the CSFM alphas decrease by more than controlling for the equal-weighted factor portfolio or the ZHCT factors, all alphas remain significant at the 1% level, and IRs remain large. Noteworthy is the significant loading of the strategies on the IVRV factor. This factor is among the strongest in the sample and, therefore, in the long leg of the CSFM strategies for most months. For example, IVRV is assigned a long position for 95% of months, even with only a 6-month formation period.

Overall, both TSFM and CSFM strategies yield positive and statistically significant returns and present novel investment opportunities that expand on a static, equal-weighted option factor portfolio and prominent low-dimensional option factor models. In addition, we can verify these baseline results for various subsamples of our sample period from 1999 to 2021. We obtain significantly positive HVX-alphas for the large majority of formation period specifications when splitting the sample period into 2 halves, distinguishing between NBER recessions and expansions, as well as assessing periods of high and low investor sentiment (Baker and Wurgler (2006)) and intermediary capital constraints (He, Kelly, and Manela (2017)).[7] We provide details on the subsample analysis in Table E.1 in the Supplementary Material.

IV. The Drivers of Option Factor Momentum

After having demonstrated the significant performance of option factor momentum strategies in the previous analyses, we turn to investigate the underlying sources of momentum effects inherent in option factors more closely.

As alluded to in Section II.C, autocorrelation in factor returns can drive factor momentum. Although the strong autocorrelation displayed in our option factor returns indicates momentum, it is not the only potential source of positive momentum returns. Conrad and Kaul (1998) stress that profitable momentum strategies do not solely arise from serial correlation in asset returns, but also from variation across unconditional mean returns of individual assets. Consequently, differences in mean returns result in CSM effects due to purchasing permanent winners and selling permanent losers. Moreover, *consistently* low or high asset returns can drive TSM effects as assets that were profitable (unprofitable) in the past will continue to be profitable (unprofitable) in the future. Hence, despite evidence of considerable autocorrelation in option factors up to 1 year, as depicted in Figure 1, the high mean returns and the substantial differences in mean returns of our factor set reported in Table 1 might likewise explain positive returns of option factor

[7]We obtain the sentiment index data from Jeffrey Wurgler's website (https://pages.stern.nyu.edu/~jwurgler/) and intermediary capital ratios from Zhiguo He's website (https://zhiguohe.net/data-and-empirical-patterns/intermediary-capital-ratio-and-risk-factor/).

momentum strategies. Consequently, both return autocorrelation and mean returns might a priori cause positive factor momentum returns in the options market.

If mean returns are the dominant drivers of option factor momentum, factors with absolute high (low) mean returns would be permanent or at least frequent constituents of the momentum strategies' long (short) leg. We show that this pattern largely holds for our option factors.

Figure 3 depicts the percentage of months within our sample period during which a factor is included in the long leg of a factor momentum strategy. Red (blue) indicates factors frequently in the long (short) leg.

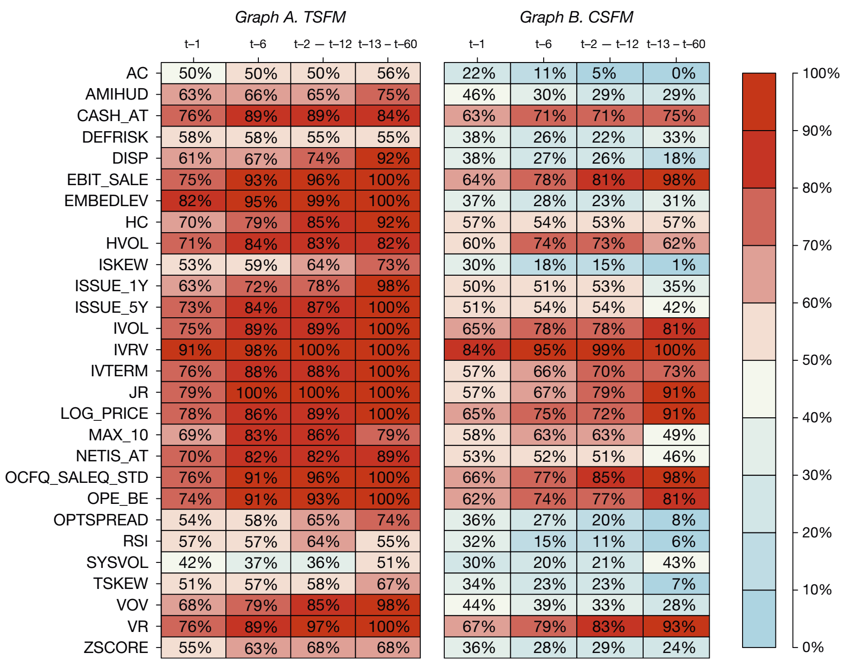
For the TSFM strategy in Panel a, most factors across different formation periods are in the long leg during more than 50% of the months in our sample period. Importantly, high-mean factors such as IVRV or the VR factor tend to be assigned to the TSFM long leg during almost all months, especially for longer formation periods. Therefore, the high performance of the TSFM strategy might not exclusively be due to autocorrelation in factor returns but due to the highly positive returns of factors included in the strategy's long leg.

Turning to CSFM in Panel B of Figure 3, note that there is no constructional long bias as the strategy's setup ensures that the same number of factors are always in the long and short leg. Nevertheless, we observe that a handful of factors, such as IVRV, are predominantly part of the CSFM long leg. This insight highlights that

FIGURE 3

Factors' Percentage Share of Being Included in Momentum Long Legs

Figure 3 shows the percentage of months during which individual factors are part of the long leg in option factor momentum strategies over various formation periods. Detailed descriptions of the characteristics used for factor construction are documented in Section B of the Supplementary Material.



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certain factors tend to consistently outperform relative to their peers and are thus frequently included in the strategy's long leg. Thus, option factor momentum in the cross-section might also be considerably attributable to strong variation in mean factor returns and not solely autocorrelation.

Although the insights from Figure 3 provide tentative evidence of the importance of mean factor returns for factor momentum strategies, it is still difficult to rule out the role of return autocorrelation. The distinction between these two return drivers is relevant within our option setting as some high-mean factors, such as IVRV, are also among the factors whose returns are among the most serially correlated (see Figure 1). Therefore, to more formally examine the extent to which option factor momentum is driven by serial correlation or factor premia, we employ several formal momentum return decompositions proposed in the literature.

A. Theoretical Factor Momentum Decompositions

Consider a hypothetical cross-sectional (factor) momentum strategy defined as

$$R_t^{LM} = \frac{1}{N}\sum_{i=1}^{N}\left(F_{i,-t} - \overline{F}_{-t}\right)F_{i,t}. \tag{5}$$

For this strategy, at the end of each month t, we weigh individual factor returns $F_{i,t}$ by the difference between the respective factor's return during the formation period $-t$ and the cross-sectional mean factor return $\overline{F}_{-t}$ in $-t$. Note that this strategy does *not* correspond to our CSFM strategy defined in equation (4), and we solely consider it to apply the corresponding return decomposition presented below. Taking the expectation of the strategy in equation (5), Lo and MacKinlay (1990)[8] show that the following equation holds:

$$\mathbb{E}\left[R_t^{LM}\right] = \underbrace{\frac{N-1}{N^2}\mathrm{Tr}(\Omega)}_{\text{Autocovariance}} - \underbrace{\frac{1}{N^2}\left(\vec{1}'\Omega\vec{1} - \mathrm{Tr}(\Omega)\right)}_{\text{Cross-serial covariance}} + \underbrace{\mathrm{Var}\left[\mu^F\right]}_{\text{Variation in means}}, \tag{6}$$

where μ^F is the vector of unconditional mean factor returns, $\mathrm{Var}[\mu^F]$ is the cross-sectional variance of mean returns, $\Omega = \mathbb{E}\left[(F_{i,t} - \mu^F)'(F_{i,t-} - \mu^F)\right]$ is the autocovariance matrix of option factor returns, $\vec{1}$ is a vector of ones, and $\mathrm{Tr}(\Omega)$ is the trace of Ω. As highlighted in equation (6), the Lo–MacKinlay decomposition splits the expected return of the LM strategy into 3 distinct components. First, positive autocovariance in individual factor returns indicates a high (low) return following a positive (negative) past return signal. Second, negative cross-serial correlations between different factor returns positively contribute to momentum profits as a positive (negative) past return on one factor signals low (high) returns on other

[8]Henceforth, the abbreviation "LM" refers to the decomposition of cross-sectional momentum proposed by Lo and MacKinlay (1990) and its underlying strategy in equation (5).

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factors. Third, as represented by the cross-sectional variance of mean factor returns, some factors with high (low) expected returns persistently earn higher (lower) returns than others.

Analogously, Moskowitz et al. (2012)[9] propose a decomposition of a (hypothetical) TSM strategy that linearly weighs individual asset returns by their average return over the formation period,

$$R_t^{MOP} = \frac{1}{N}\sum_{i=1}^{N} F_{i,-t}F_{i,t}. \tag{7}$$

After taking expectations, the strategy in equation (7) decomposes into

$$\mathbb{E}\left[R_t^{MOP}\right] = \underbrace{\frac{\text{Tr}(\Omega)}{N}}_{\text{Autocovariance}} + \underbrace{\frac{\mu^{F\prime}\mu^F}{N}}_{\text{Squared mean effect}}. \tag{8}$$

The first term of the MOP decomposition again captures the autocorrelation of individual factors. The second term represents the dependency of the TSM strategy on mean returns. If absolute factor returns are persistently high, TSM is profitable as the strategy's long (short) positions tend to be long (short) in factors with persistently high (low) returns.

We provide details on the empirical implementation of both decompositions and computation of bootstrapped standard errors in Section C.1 of the Supplementary Material. Table 3 depicts the results.

Up to a formation period of 1 year and in line with Ehsani and Linnainmaa (2022) and Arnott et al. (2023) for stock factor momentum, we observe positive cross-serial covariance terms that *negatively* influence the cross-sectional LM strategy in Panel A. The statistical significance of these terms remains modest with t-statistics between -2 and -3.

The autocovariance terms of both decompositions are the same and only scaled differently. The t-statistics of the autocovariance estimates range between 3.60 and 4.96 for the formation periods up to 1 year. The autocovariance term is only a borderline significant contributor (t-stat: 1.95) to the strategy returns for the long-term horizon of $t-13$ to $t-60$. The economic magnitudes of the decomposition terms suggest similar insights.

Importantly, mean factor returns are a key component of momentum strategies next to the autocovariance in factor returns. With longer formation periods, the variation and sum of squared returns increase in magnitude and statistical significance. This observation is unsurprising, considering that the formation period returns more closely resemble the respective unconditional means for longer periods. However, the decomposition terms related to mean factor returns also significantly contribute to momentum strategies for short-term formation periods. Only the estimate of variation in mean returns for the $t-1$ LM strategy

[9]Henceforth, the abbreviation "MOP" refers to the decomposition of time-series momentum proposed by Moskowitz, Ooi, and Pedersen (2012) and its underlying strategy in equation (7).

TABLE 3

Decompositions of Option Factor Momentum Strategies

Table 3 reports empirical estimates for the cross-sectional and time-series momentum decompositions as proposed by Lo and MacKinlay (1990) (LM, Panel A) and Moskowitz et al. (2012) (MOP, Panel B). We apply block bootstrapping with a block length of 4 to mimic the autocorrelation-robust Newey–West standard errors with 4 lags. Details on the empirical implementation are in Section C.1 of the Supplementary Material. The sample period is from Jan. 1999 to Dec. 2021. All returns are annualized and in percentages.

	t–1	t–6	t–2 to t–12	t–13 to t–60
Panel A. Cross-Sectional Factor Momentum				
Autocovariance	5.37	7.86	7.92	2.29
	(3.60)	(4.96)	(4.76)	(1.95)
− Cross-serial covariance	−1.62	−2.28	−2.27	0.36
	(−2.10)	(−2.65)	(−2.54)	(0.66)
+ Variation in mean returns	2.28	4.32	5.40	10.63
	(1.97)	(3.65)	(4.30)	(10.31)
= Cross-sectional option factor momentum (LM)	6.03	9.89	11.05	13.28
	(4.49)	(6.02)	(5.93)	(8.41)
Panel B. Time-Series Factor Momentum				
Autocovariance	3.63	4.96	4.66	1.19
	(3.60)	(4.96)	(4.76)	(1.95)
+ Sum of squared mean returns	3.84	6.70	7.70	13.81
	(3.80)	(6.70)	(7.86)	(22.61)
= Time-series option factor momentum (MOP)	7.47	11.66	12.36	15.00
	(5.02)	(6.09)	(6.23)	(9.92)

exhibits a low t-statistic of 1.97. Also, compared to the LM decomposition, mean returns are generally a stronger contributor to momentum for the time-series MOP strategies, where their significance is at least as high as for the autocovariance term.

Overall, we conclude that high mean factor returns are a dominant driver of option factor momentum strategies. Autocorrelation still plays a considerable role in explaining option factor momentum, especially for the CSM strategy. The fact that both mean returns and autocorrelation are essential in explaining the origin of momentum in option factors is a stark contrast to analogous analyses for the stock market. For example, Ehsani and Linnainmaa (2022) find that for formation periods of 1 year, the factor return autocovariance is predominantly responsible for positive stock factor momentum strategies. Option factor momentum, especially in the time-series dimension, stems from high and persistent mean factor returns for the same formation period.

B. Factor Timing Versus Factor Persistence

As the time-series option MOP strategy, in particular, sets itself apart from its stock factor counterpart in terms of reliance on mean factor returns, we consider an additional analysis of time-series option factor momentum proposed by Leippold and Yang (2021). Importantly, the authors point out that the MOP strategy underestimates the true impact of mean factor returns. Instead of breaking down the hypothetical MOP strategy, Leippold and Yang (2021) derive a decomposition of the baseline TSFM strategy from equation (3) into a factor timing (FT),

(9) $$R_t^{FT} = \frac{2}{N}\sum_{i=1}^{N} \operatorname{sign}\left(F_{i,-t} - \overline{F}_{i,t-1}\right) F_{i,t},$$

and a buy-and-hold (BH) strategy,

(10) $$R_t^{BH} = \frac{2}{N}\sum_{i=1}^{N} \operatorname{sign}\left(\overline{F}_{i,t-1}\right) F_{i,t},$$

where $\overline{F}_{i,t-1}$ is the prevailing historical mean factor return up to month $t-1$.

FT is long (short) in factors that outperform (underperform) their prevailing mean return during the formation period. BH is long (short) in factors that have a positive (negative) prevailing mean return. Notably, BH tends to perform well if factor returns are persistently positive or negative, corresponding to large absolute mean factor returns. In this sense, BH is strongly related to the second term of the MOP decomposition in equation (8). Moreover, as our expanding window approach to determine factor sorting directions leads to factors with positive prevailing mean until momentum strategies are constructed, note that BH is a long-only portfolio and equivalent to the equal-weighted factor portfolio, EW_FAC, introduced in Section III. In contrast, FT represents the continuation of factor returns over time and is, therefore, conceptually more closely related to the autocovariance term in equation (8). Leippold and Yang (2021) show that expected TSM returns of *individual factors* can be expressed as a linear combination of individual FT and BH returns (i.e., the terms within the summations for factor i).

In Panel A of Table 4, we separately depict the returns and Sharpe ratios of the BH and FT strategies over different formation periods.

The annualized mean returns of the BH strategy are positive with 13.95% (t-stat: 9.28). The FT strategies based on formation periods up to 1 year display mean returns ranging from 3.52% to 4.05% with t-statistics up to 2.72. Only for the formation period $t-13$ to $t-60$, FT yields a negative mean return. The Sharpe ratios of option FT strategies are still sizeable for the formation periods up to 1 year, ranging from 0.67 to 0.8.

We regress TSFM returns on either strategy's return in Panel B of Table 4. Judging by the significance of the regression alphas, we find that TSFM is largely explained by BH. The alpha coefficient remains statistically significant and decreases noticeably in terms of economic magnitude and statistical significance compared to the strategy's mean returns presented in Table 2. Nonetheless, as BH does not fully subsume the returns of the TSFM strategy, and analogous to the results in Panel B of Table 2 for EW_FAC, we can conclude that TSFM remains a distinct strategy from a mere buy-and-hold approach. On the other hand, after regressing TSFM on FT returns, alphas only decrease slightly, and significance levels even increase compared to our baseline results in Table 2.

It must be noted that even the pure factor timing strategy FT might not always successfully profit from existing autocorrelation. Consider again the definition of FT in equation (9). One precondition for FT to capture return innovations is that the

TABLE 4

Buy-and-Hold and Factor Timing Strategies with Option Factors

Table 4 Panel A reports mean and Sharpe ratios (SR) for buy-and-hold (BH) and factor timing (FT) strategies over different formation periods using option factors. BH is the return of a strategy that is long (short) in factors with a positive (negative) prevailing mean return. FT is a strategy that is long (short) in factors that have outperformed their prevailing mean return up to $t-1$ during the respective formation period. To assess whether either BH or FT can subsume TSFM, we regress TSFM returns on either BH or FT returns (as denoted by the superscript k) in Panel B. t-statistics (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag 4, following Newey and West (1987). We estimate SR standard errors using GMM. The sample period is from Jan. 1999 to Dec. 2021. All returns are annualized and in percentages. (*) indicates that we only report the summary statistics for the BH returns beginning after the years 1996–1998 consistent with our expanding window approach that utilizes the first 3 years as a burn-in period to determine factor signs.

	k = BH (Buy-and-Hold)				k = FT (Factor Timing)			
	t–1	t–6	t–2 to t–12	t–13 to t–60	t–1	t–6	t–2 to t–12	t–13 to t–60
Panel A. Summary								
Mean return			13.95*		3.59	4.05	3.52	−1.70
			(9.28)		(2.72)	(2.57)	(2.27)	(−1.75)
Sharpe ratio			2.74		0.67	0.80	0.77	−0.53
			(9.83)		(3.35)	(3.22)	(2.66)	(−1.78)
Panel B. Regression $R_t^{TSFM} = \alpha + \beta R_t^k + \varepsilon_t$								
α	3.65	5.19	4.63	1.22	7.46	11.86	12.76	12.62
	(2.37)	(3.40)	(3.64)	(1.44)	(12.87)	(15.31)	(13.40)	(10.11)
β	0.49	0.64	0.72	0.85	0.85	0.57	0.52	0.31
	(5.13)	(6.51)	(10.05)	(14.42)	(28.55)	(6.32)	(4.40)	(1.48)
R^2	0.24	0.51	0.63	0.85	0.79	0.40	0.27	0.05

prevailing historical mean, $\overline{F}_{i,t-1}$, is stable over time. In this context, it is necessary to point out that some high-mean factors, such as IVRV, display higher mean returns in the earlier parts of our sample periods until the early 2000s.[10] For the factors with the highest full-sample mean returns in Panel A, most prominently IVRV, we document that these factors yield higher returns during earlier periods. Thus, for large parts of the sample period, the FT strategy tends to be short in high-mean factors that can no longer beat their $\overline{F}_{i,t-1}$ benchmark but would otherwise have positively contributed to FT returns based on their displayed autocorrelation. Moreover, as option factors tend to display rather low return volatility, it is unlikely that strong return fluctuations can overcome the changes in mean returns, leading to prevailing historical means dominating the formation signal.

Nevertheless, the stronger performance and higher explanatory power of BH over FT point to a dominant role or high mean factor returns for TSFM, especially for longer formation periods.

V. Option Momentum and Option Factor Momentum

In this section, we investigate the relation between factor momentum and momentum in single-name option returns. Heston et al. (2023) document strong momentum effects in returns of at-the-money straddles on individual equities. We construct time-series and cross-sectional option momentum strategies in delta-hedged call options analogous to our baseline strategies outlined in equations (3)

[10]We plot 36-month rolling mean factor returns in Figure E.1 in the Supplementary Material.

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and (4). Following Heston et al. (2023), we require return observations for two-thirds of the months during a formation period. Using delta-hedged call returns instead of straddles deviates from the construction of option momentum in Heston et al. (2023). However, we do not expect a vastly different return behavior, as both straddles and delta-hedged calls are roughly delta-neutral and a bet on future realized versus implied volatility of the underlying.

Panel A of Table 5 summarizes the performance of option momentum (OM) in daily delta-hedged call positions. Except for the long-term horizon time-series strategy, both time-series option momentum (TSM) and cross-sectional option momentum (CSM) strategies yield, on average, positive returns, albeit smaller in economic magnitude and statistical significance than our factor momentum strategies. We obtain insignificant mean returns for the longer-term horizon momentum strategies when performing a risk adjustment using the HVX factor model, depicted in Panel B of Table 5. However, despite decreases in magnitude and significance, the alphas of strategies with shorter formation periods remain largely positive and statistically significant. Notably, the alphas of the TSM strategies are larger than the corresponding CSM alphas. The CSM strategy for the 6-month formation period with a t-statistic of 3.22 exhibits the most statistically significant alpha.

Having extended the findings of Heston et al. (2023) to delta-hedged call returns instead of straddles, we next investigate whether option factor momentum spans option momentum.

TABLE 5

Option Momentum Returns

Table 5 reports performance measures of both time-series momentum (TSM) and cross-sectional momentum (CSM) strategies based on 8 formation periods. All strategies are built from daily delta-hedged call option returns from Jan. 1999 to Dec. 2021. TSM strategies go long (short) in options with positive (negative) formation period returns. CSM strategies go long (short) in options with an above (below) median return in the formation period. For each underlying company, we require return observations for at least two-thirds of the months of the formation period. Panel A provides a summary of Option Momentum strategies. Panel B reports the results of regressing TSM and CSM on factors based on the model by Horenstein et al. (2022) (HVX): the equal-weighted return of 280 portfolios that arise from the decile sorts on our 28 characteristics (EW_RET), the long-short factor based on the volatility of implied volatility (VOV), and the long-short factor based on the difference in implied and realized volatility (IVRV). Mean returns, Sharpe ratios, and alphas are annualized and given in percentages. t-statistics (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag 4, following Newey and West (1987).

	Time-Series Momentum				Cross-Sectional Momentum			
	t–1	t–6	t–2 to t–12	t–13 to t–60	t–1	t–6	t–2 to t–12	t–13 to t–60
Panel A. Performance of Option Momentum								
Mean return	6.27	4.90	4.45	0.74	2.88	3.92	4.57	1.85
	(4.70)	(5.47)	(4.04)	(0.84)	(4.46)	(7.07)	(6.98)	(4.60)
Sharpe ratio	0.99	1.22	1.02	0.19	1.32	2.03	2.03	1.08
	(6.32)	(5.17)	(3.84)	(0.80)	(6.55)	(10.28)	(10.79)	(5.03)
Panel B. Option Momentum Versus HVX Factors								
α	4.45	5.05	3.34	−1.93	1.41	1.95	1.27	0.30
	(2.97)	(3.12)	(1.96)	(−1.23)	(2.22)	(3.22)	(1.82)	(0.52)
EW_RET	0.28	0.01	−0.01	−0.03	0.07	0.10	0.10	0.10
	(1.22)	(0.07)	(−0.10)	(−0.21)	(1.70)	(2.46)	(2.55)	(5.00)
VOV	−0.30	−0.09	−0.08	−0.08	−0.08	−0.03	0.00	−0.04
	(−2.38)	(−1.06)	(−1.07)	(−0.98)	(−2.35)	(−0.91)	(−0.07)	(−1.55)
IVRV	0.13	0.01	0.05	0.13	0.07	0.08	0.13	0.08
	(2.67)	(0.22)	(1.02)	(2.43)	(2.57)	(3.63)	(4.68)	(4.31)
R^2	0.13	0.01	0.01	0.04	0.10	0.19	0.25	0.19

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In Panel A of Table 6, we show the results of regressing option momentum returns on the corresponding option factor momentum returns. Regression alphas tend to become insignificant and, in 3 cases, even negative, except for CSM with the formation periods $t-6$ and $t-2$ to $t-12$. However, all alphas turn insignificant after additionally controlling for the HVX factors in Panel B. On the other hand, when controlling for option momentum in Panel C and for option momentum plus the HVX factors in Panel D, option factor momentum alphas remain significantly

TABLE 6

Option Momentum Versus Option Factor Momentum

Panel A and Panel B of Table 6 report the results regressing option momentum (OM) on the factor momentum strategy with the same formation period and on the Horenstein et al. (2022) model augmented by factor momentum strategy. Panel C and Panel D report results of identical regressions but switching factor momentum (FM) and option momentum (OM). The respective regression equations are stated above the results. Regression intercepts (α) are annualized and given in percentages. t-statistics (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag 4, following Newey and West (1987).The sample period is from Jan. 1999 to Dec. 2021.

	Time-Series Momentum				Cross-Sectional Momentum			
	$t-1$	$t-6$	$t-2$ to $t-12$	$t-13$ to $t-60$	$t-1$	$t-6$	$t-2$ to $t-12$	$t-13$ to $t-60$
Panel A. Regression $R_t^{OM}=\alpha+\beta R_t^{FM}+\varepsilon_t$								
α	−0.54	−0.33	2.10	−2.35	0.69	1.20	1.01	0.65
	(−0.49)	(−0.33)	(1.31)	(−1.30)	(1.45)	(2.37)	(1.97)	(1.18)
R_{FM}	0.65	0.37	0.16	0.26	0.34	0.30	0.37	0.17
	(4.80)	(5.86)	(1.69)	(1.98)	(6.98)	(4.52)	(5.12)	(3.39)
R^2	0.28	0.18	0.03	0.09	0.34	0.26	0.29	0.09
Panel B. Regression $R_t^{OM}=\alpha+\beta_1 R_t^{FM}+\beta_2 \text{EW\_RET}_t+\beta_3 \text{VOV}_t+\beta_4 \text{IVRV}_t+\varepsilon_t$								
α	0.07	1.03	2.06	−3.53	0.17	0.76	0.26	−0.38
	(0.06)	(0.85)	(1.23)	(−2.07)	(0.27)	(1.28)	(0.39)	(−0.67)
R_{FM}	0.66	0.47	0.20	0.27	0.31	0.25	0.27	0.16
	(6.99)	(6.08)	(1.32)	(2.39)	(7.13)	(3.91)	(3.94)	(4.44)
EW_RET	0.30	0.07	0.01	0.02	0.04	0.07	0.07	0.10
	(1.68)	(0.72)	(0.06)	(0.16)	(0.85)	(2.00)	(1.58)	(6.50)
VOV	−0.31	−0.20	−0.12	−0.14	−0.06	−0.05	−0.02	−0.03
	(−3.61)	(−3.06)	(−1.15)	(−1.72)	(−1.89)	(−1.32)	(−0.41)	(−1.31)
IVRV	0.04	−0.06	0.00	0.07	0.04	0.04	0.07	0.06
	(1.21)	(−1.42)	(0.08)	(1.32)	(1.80)	(2.21)	(3.29)	(2.73)
R^2	0.41	0.25	0.04	0.12	0.38	0.35	0.35	0.26
Panel C. Regression $R_t^{FM}=\alpha+\beta R_t^{OM}+\varepsilon_t$								
α	7.83	11.81	13.81	11.87	3.54	5.68	5.97	6.01
	(7.34)	(10.06)	(9.15)	(8.95)	(4.71)	(7.82)	(8.31)	(11.04)
R_{OM}	0.43	0.48	0.18	0.34	1.01	0.89	0.77	0.51
	(4.12)	(4.63)	(1.76)	(2.56)	(5.81)	(7.51)	(8.46)	(3.16)
R^2	0.28	0.18	0.03	0.09	0.34	0.26	0.29	0.09
Panel D. Regression $R_t^{FM}=\alpha+\beta_1 R_t^{OM}+\beta_2 \text{EW\_RET}_t+\beta_3 \text{VOV}_t+\beta_4 \text{IVRV}_t+\varepsilon_t$								
α	4.44	5.90	5.98	6.44	2.59	3.27	3.13	4.16
	(4.22)	(5.18)	(4.59)	(4.53)	(2.90)	(3.66)	(3.96)	(3.43)
R_{OM}	0.48	0.51	0.16	0.29	0.97	0.78	0.52	0.53
	(5.49)	(6.80)	(1.46)	(1.96)	(5.19)	(5.19)	(4.42)	(4.12)
EW_RET	−0.17	−0.13	−0.11	−0.20	0.03	0.02	0.07	−0.10
	(−3.00)	(−1.53)	(−0.76)	(−1.19)	(0.37)	(0.33)	(1.08)	(−0.99)
VOV	0.16	0.28	0.24	0.26	0.01	0.09	0.05	−0.06
	(1.29)	(2.12)	(1.68)	(2.07)	(0.16)	(1.46)	(0.87)	(−0.95)
IVRV	0.07	0.15	0.24	0.17	0.04	0.09	0.14	0.08
	(1.97)	(3.94)	(5.60)	(2.27)	(1.12)	(3.05)	(4.40)	(1.39)
R^2	0.35	0.38	0.30	0.30	0.35	0.32	0.40	0.16

positive at high confidence levels. Contrary to Heston et al. (2023) but in line with findings of Ehsani and Linnainmaa (2022) for the stock market, we show that factor momentum based on our 28 option factors subsumes option momentum.[11] Moreover, Tian and Wu (2023) interpret CSM in single options as a historical risk premium that reflects persistence in the risk magnitude variations of risk sources that drive option returns. Similarly, TSM indicates persistent risk magnitude levels in the options market. As option factor momentum tends to subsume single-option momentum and mean factor returns play a relevant role in the factor momentum strategies according to the decompositions in the previous section, our findings fall in line with the view of single-option momentum as a historical risk premium captured by option factor momentum.

VI. Additional Analyses and Robustness Checks

In this section, we discuss the results of various additional analyses. We investigate if time-series factor momentum spans CSFM and vice versa, document PC momentum, and construct momentum strategies according to Gupta and Kelly (2019). We conclude with additional robustness checks.

A. Time-Series Versus Cross-Sectional Factor Momentum

First, we compare the performance of our TSFM and CSFM strategies by conducting spanning tests. TSM was proposed by Moskowitz et al. (2012) as a purer bet on assets' autocorrelation compared to CSM. Suffering from positive cross-serial correlation, Moskowitz et al. (2012) find that TSM subsumes CSM but not vice versa. Following Leippold and Yang (2021), we treat both our TSFM and CSFM as zero-cost strategies because the underlying factors are by construction zero-cost strategies. Thus we do not enhance CSFM with a time-varying long position in an equal-weighted (factor) portfolio as proposed by Goyal and Jegadeesh (2018).

We present the results of pairwise spanning regressions in Table 7, with TSFM returns being the dependent variable on the left-hand panel. Our strategies are strongly related, as indicated by high t-statistics on the slope coefficients and high R^2 of up to 0.71 for the 1-month formation period strategies. Nevertheless, 6 out of 8 strategies produce positive alphas at the 5% significance level, providing evidence that TSFM and CSFM are partly distinct phenomena in the options market. Only for the 1-month and 5-year formation periods is CSFM fully subsumed by TSFM. As shown in Table 3, CSFM is adversely impacted by positive cross-serial correlation, introducing noise and reducing its ability to capture returns based on factors' own return continuation. Consequently, TSFM demonstrates a more robust and reliable approach for shorter formation periods. Our findings contrast Arnott et al. (2023), who show that their stock CSFM strategy is distinct from the stock TSFM strategy by Ehsani and Linnainmaa (2022). However, the stock TSFM strategy is based on a 1-year formation period, while the stock CSFM strategy is based on a 1-month formation period. Instead, we compare strategies with identical formation periods

[11]Heston et al. (2023) rely on a time-series momentum strategy built from seven option straddle factors. On the contrary, we consider time-series and cross-sectional option momentum strategies and a set of 28 option factors.

TABLE 7

Time-Series Versus Cross-Sectional Factor Momentum

Table 7 reports the results of regressing TSFM and CSFM strategies (with identical formation periods) on each other. TSFM strategy returns are the dependent variable on the left-hand side of the table. Regression intercepts (α) are annualized and given in percentages. t-statistics (in parentheses) account for heteroskedasticity and autocorrelation in residuals up to lag 4, following Newey and West (1987). The sample period is from Jan. 1999 to Dec. 2021.

	Time-Series Factor Momentum				Cross-Sectional Factor Momentum			
	t–1	t–6	t–2 to t–12	t–13 to t–60	t–1	t–6	t–2 to t–12	t–13 to t–60
α	3.09	5.17	4.48	4.11	−0.02	1.78	1.81	1.16
	(4.77)	(5.47)	(4.39)	(3.08)	(−0.03)	(1.93)	(2.14)	(1.59)
CSFM	1.15	0.98	1.06	1.15				
	(12.63)	(7.76)	(9.44)	(8.79)				
TSFM					0.62	0.52	0.53	0.48
					(7.62)	(7.24)	(8.24)	(6.73)
R^2	0.71	0.51	0.56	0.55	0.71	0.51	0.56	0.55

to accurately compare the performances, leading to higher mutual explanatory power.

B. PC Momentum

Following a model by Kozak, Nagel, and Santosh (2018), Ehsani and Linnainmaa (2022) show that persistent sentiment-driven excess demand of investors can lead to positive autocovariance in factor returns. The authors argue that in the absence of near arbitrage, rational arbitrageurs will only trade against sentiment demand in low-eigenvalue PCs as trading in high-eigenvalue PCs carries high systematic risks. Therefore, momentum effects should only remain in high-eigenvalue PCs. In line with the model, Ehsani and Linnainmaa (2022) find that a TSFM strategy trading the factors' largest 10 PCs ordered by eigenvalues subsumes most momentum in the other subset of PCs and can explain momentum in stocks. We extend these tests to our option factor sample. The empirical implementation is detailed in Section C.2 of the Supplementary Material.

In Panel A of Table 8, we report the mean returns of both the TSFM and the CSFM strategies based on subsets of 7 PCs. In line with the findings for equity market factors, profits are the highest and most statistically significant in the 7 largest PCs, with t-statistics ranging from 5.38 to 11.93. Nevertheless, all other subsets also yield positive and significant momentum profits for most or all formation periods. This result does not immediately contradict the results of Ehsani and Linnainmaa (2022) and Arnott et al. (2023), who find momentum in lower-eigenvalue PCs as well. However, momentum in high-eigenvalue PCs fully explains lower-eigenvalue PC momentum in these studies. We test for this effect by regressing returns of lower PC subset strategies on their respective PC_{1-7} counterpart. Alphas are reported in Panel B of Table 8. Some positive and significant returns remain. This suggests that there are momentum effects in lower eigenvalue PCs, which are distinct from the momentum effects of the largest 7 PCs. Nevertheless, for the lowest eigenvalue PC subset, no significant alphas remain, and for the others, significance and magnitude drop substantially. Overall, our results suggest that the highest-eigenvalue PCs exhibit the strongest factor

TABLE 8

Momentum in Option Factors' Principal Components

Table 8 reports the mean returns of TSFM and CSFM strategies based on the principal components (PCs) of 28 option factors. The empirical construction of PC portfolios is detailed in Section C.2 of the Supplementary Material. We construct TSFM and CSFM strategies using subsets of 7 PCs and save returns for month t. We take 120 months of factor returns to perform the first PC analysis. Therefore, the PC momentum returns range from Feb. 2006 to Dec. 2021. In Panel A, we report annualized mean momentum returns in percentages for different subsets of PCs. For example, PC_{1-7} denotes the subset of the largest 7 PCs ordered by eigenvalue. In Panel B, we report the annualized alphas after controlling for the returns of the PC_{1-7} subset with the identical formation period. t-statistics of mean returns and alphas account for heteroskedasticity and autocorrelation in residuals up to lag 4, following Newey and West (1987).

	Time-Series Factor Momentum				Cross-Sectional Factor Momentum			
	t–1	t–6	t–2 to t–12	t–13 to t–60	t–1	t–6	t–2 to t–12	t–13 to t–60
Panel A. Mean PC Momentum Returns								
PC_{1-7}	9.47	12.17	10.48	9.19	7.80	8.90	7.46	6.03
	(8.05)	(11.93)	(9.05)	(7.60)	(5.99)	(8.43)	(6.93)	(5.38)
PC_{8-14}	1.60	6.11	5.07	3.18	3.02	6.91	5.12	4.26
	(1.72)	(4.79)	(4.64)	(2.56)	(2.76)	(5.57)	(4.89)	(3.80)
PC_{15-21}	2.10	4.65	5.39	2.94	1.57	4.76	4.33	3.42
	(2.15)	(3.91)	(5.37)	(2.66)	(1.87)	(4.44)	(4.22)	(3.42)
PC_{22-28}	3.32	5.38	3.48	1.35	2.95	4.51	3.40	1.21
	(2.81)	(4.24)	(2.80)	(0.84)	(2.17)	(3.42)	(2.24)	(0.79)
Panel B. Alphas After Adjusting for PC_{1-7} Momentum								
PC_{8-14}	0.63	2.56	2.49	0.39	2.55	3.95	3.42	2.14
	(0.60)	(1.75)	(1.88)	(0.20)	(2.07)	(3.28)	(2.87)	(1.30)
PC_{15-21}	1.41	1.29	2.76	1.51	2.09	5.28	2.85	3.12
	(1.02)	(0.79)	(2.23)	(0.80)	(2.20)	(3.46)	(1.62)	(2.82)
PC_{22-28}	0.10	−0.36	2.44	−0.96	−0.06	0.94	2.69	2.13
	(0.08)	(−0.19)	(1.59)	(−0.48)	(−0.04)	(0.51)	(1.72)	(1.57)

momentum, and are thus largely in line with Ehsani and Linnainmaa (2022) and Arnott et al. (2023).

Finally, we test the ability of momentum effects in high and low-eigenvalue PCs to explain single-option momentum. To do so, we follow Arnott et al. (2023) and construct PC momentum strategies, first built from only 2 PCs and then adding PCs until the full sample of 28 PCs is reached. We then regress option momentum returns on these various PC momentum strategies and report t-statistics of the regression intercepts in Figure 4.

For the black lines, we start constructing momentum strategies with the 2 highest eigenvalue PCs and consequentially add further PCs ordered from high to low eigenvalues. For the red lines, we start with the 2 lowest eigenvalue PCs. We show t-statistics of time-series and cross-sectional option momentum alphas for 2 formation periods: 1 month and 1 year, excluding the most recent month. Generally, we see that t-statistics decrease much faster when starting with the highest eigenvalue PCs. The red lines show that t-statistics decrease very little when controlling for momentum effects in the lowest eigenvalue PCs. This observation provides evidence that momentum effects in PCs lie in high-eigenvalue rather than low-eigenvalue PCs.

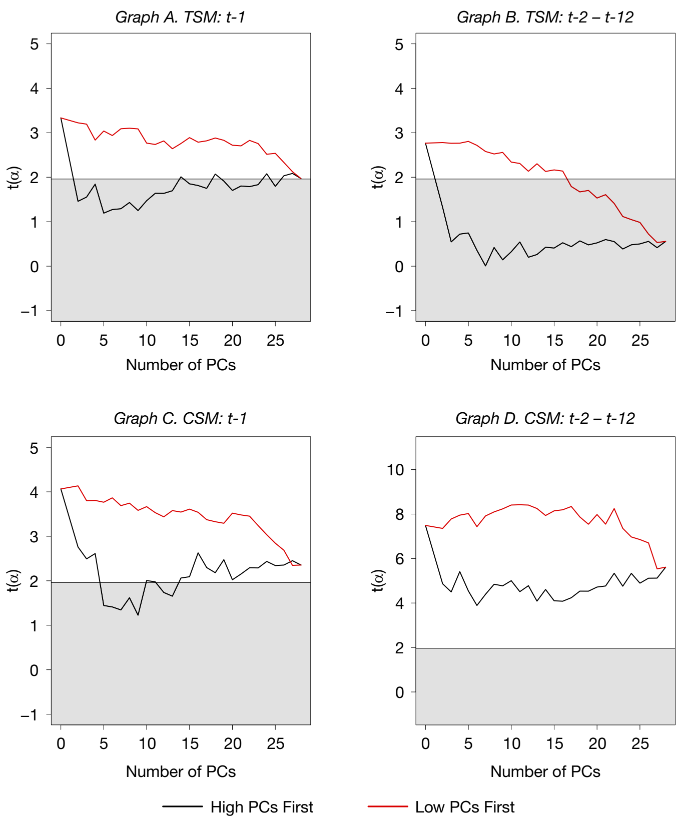
C. Alternative Momentum Construction

One shortcoming of our baseline momentum strategies is that some factors are almost always assigned the same $\pm\ 2/N$ portfolio weight because these factors are

FIGURE 4

Significance of Option Momentum After Controlling for PC Momentum

Figure 4 shows t-statistics of regression alphas estimated from regressing time-series (TSM) and cross-sectional (CSM) option momentum returns on the returns of PC momentum strategies. For the black lines, we construct PC momentum strategies from the highest-eigenvalue PCs of our set of 28 option factors and add lower-eigenvalue PCs going from left to right. For the red lines, we start with the lowest-eigenvalue PCs. The number of PCs from which the PC momentum strategies are built is shown on the x-axis. For $x=0$, we depict t-statistics of the raw mean option momentum returns. All t-statistics account for heteroskedasticity and autocorrelation in residuals up to lag 4, following Newey and West (1987).



persistently strong (weak). In such cases, a factor's autocorrelation does not play a role and is not reflected in the TSFM and CSFM strategies. We follow Gupta and Kelly (2019) to address these issues and construct alternative factor momentum strategies. For time-series factor momentum, we calculate a z-score factor weight defined by

$$z_{i,t} = \min\left(\max\left(\frac{1}{\sigma_{i,t}}F_{i,-t}, -2\right)2\right), \tag{11}$$

where $F_{i,-t}$ denotes the average monthly return of factor i for formation period $-t$. $\sigma_{i,t}$ denotes the monthly factor volatility over the previous 3 years for formation periods $t-1$, $t-6$, and $t-2$ to $t-12$. Following Gupta and Kelly (2019) we calculate $\sigma_{i,t}$ over 10 years for the $t-13$ to $t-60$ formation period. For cross-sectional factor momentum, we subtract the median formation period return $\tilde{F}_{-t}$ from $F_{i,-t}$ when calculating the z-scores which are capped between -2 and 2. We weigh the long and short legs by the respective positive and negative z-scores. These factor momentum strategies differ from the original strategies proposed in Section III. First, factor weights are linearly proportional to past factor performance. Thus, these strategies are more effective in capturing the autocorrelation of extremely high (low) performing factors. Second, the time-series strategy does not have a long bias, as the strategy is invested equally with $1 in both the long and the short leg.

Baseline results for the alternative factor momentum strategies are reported in Table E.2 in the Supplementary Material. Again, we find highly significant annualized mean returns ranging from 8.76% to 14.84%, high Sharpe ratios, and high alphas after controlling for the factors of Horenstein et al. (2022).

Additionally, we construct option momentum strategy in the same way as outlined in equation (11), but using options instead of factor returns. Table E.3 in the Supplementary Material shows that, especially for CSM strategies, significant alphas remain even after controlling for the HVX factors. However, after augmenting the model by Horenstein et al. (2022) with the alternative factor momentum strategies, the majority of alphas turn insignificant for the formation periods below 5 years. On the other hand, option momentum again does not subsume option factor momentum, providing further evidence that option factor momentum explains option momentum, but not vice versa.

D. Robustness Checks

We conduct robustness checks for our baseline strategies with detailed results presented in Section E of the Supplementary Material. First, we use daily delta-hedged put options instead of call options to test for both option factor momentum and option momentum (Section E.4 of the Supplementary Material). Second, for the factor construction, we weigh options within each decile portfolio by the option's underlying market capitalization (Section E.5 of the Supplementary Material). Additionally, we cut our option sample by keeping only the most liquid 50% of options each month, measuring liquidity by the options' proportional bid–ask spreads (Section E.6 of the Supplementary Material). The construction of option momentum strategies and the HVX factors are adjusted accordingly for each robustness test. In all settings, option factor momentum yields high mean returns, high Sharpe ratios, and significant alphas after controlling for the HVX factors. This holds for both TSFM and CSFM strategies and across all formation periods. Moreover, option factor momentum continues to be distinct from option momentum, while the latter is subsumed by option factor momentum.

VII. Conclusion

Factors that describe the cross-section of stock returns exhibit momentum, and through stocks' and industries' factor exposure, this momentum causes stock and industry momentum (Ehsani and Linnainmaa (2022), Arnott et al. (2023)). In this article, we extend the tests for factor momentum to the equity options market relying on a set of 28 option factors. We find corroborating evidence for both the existence of factor momentum and its explanatory power for momentum in the factors' underlying assets.

First, time-series and cross-sectional option factor momentum strategies are highly profitable. Moreover, their returns are distinct from returns of an equal-weighted factor portfolio and yield significant alphas after accounting for option factor models. Second, strategies relying on a 1-month formation period are considerably driven by factor autocorrelation. However, the longer the formation period, the more important high mean factor returns and their persistent variation as momentum drivers, especially for time-series factor momentum. This resembles a remarkable difference to stock markets. Third, spanning tests suggest that option factor momentum subsumes option momentum and not vice versa.

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109025000225.

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